

# SELF-RAG Evaluation Project

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# Original Paper: SELF-RAG

## SELF-RAG: LEARNING TO RETRIEVE, GENERATE, AND CRITIQUE THROUGH SELF-REFLECTION

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# Reflection Tokens

Type	Input	Output	Definitions
<b>Retrieval</b>	$x / x, y$	{yes, no, continue}	Decides when to retrieve with $\mathcal{R}$
<b>IsRel</b>	$x, d$	{ <b>relevant</b> , irrelevant}	$d$ provides useful information to solve $x$ .
<b>IsSup</b>	$x, d, y$	{ <b>fully supported</b> , partially supported, no support}	All of the verification-worthy statement in $y$ is supported by $d$ .
<b>IsUse</b>	$x, y$	{ <b>5</b> , 4, 3, 2, 1}	$y$ is a useful response to $x$ .

Four types of reflection tokens used in SELF-RAG. Each type uses several tokens to represent its output values. The bottom three rows are three types of **Critique** tokens, and **the bold text** indicates the most desirable critique tokens.  $x, y, d$  indicate input, output, and a relevant passage, respectively.

# Algorithm

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**Algorithm 1** SELF-RAG Inference

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**Require:** Generator LM  $\mathcal{M}$ , Retriever  $\mathcal{R}$ , Large-scale passage collections  $\{d_1, \dots, d_N\}$

- 1: **Input:** input prompt  $x$  and preceding generation  $y_{<t}$ , **Output:** next output segment  $y_t$
  - 2:  $\mathcal{M}$  predicts Retrieve given  $(x, y_{<t})$
  - 3: **if** Retrieve == Yes **then**
  - 4:     Retrieve relevant text passages  $\mathbf{D}$  using  $\mathcal{R}$  given  $(x, y_{t-1})$  ▷ Retrieve
  - 5:      $\mathcal{M}$  predicts ISREL given  $x, d$  and  $y_t$  given  $x, d, y_{<t}$  for each  $d \in \mathbf{D}$  ▷ Generate
  - 6:      $\mathcal{M}$  predicts ISSUP and ISUSE given  $x, y_t, d$  for each  $d \in \mathbf{D}$  ▷ Critique
  - 7:     Rank  $y_t$  based on ISREL, ISSUP, ISUSE ▷ Detailed in Section 3.3
  - 8: **else if** Retrieve == No **then**
  - 9:      $\mathcal{M}_{gen}$  predicts  $y_t$  given  $x$  ▷ Generate
  - 10:     $\mathcal{M}_{gen}$  predicts ISUSE given  $x, y_t$  ▷ Critique
-

# RAG vs Self-RAG

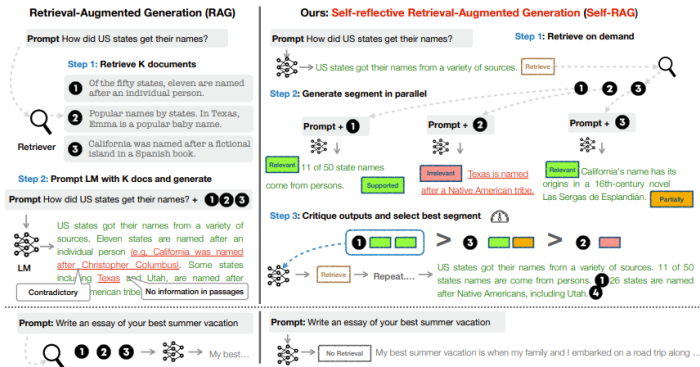


Figure 1: Overview of SELF-RAG. SELF-RAG learns to retrieve, critique, and generate text passages to enhance overall generation quality, factuality, and verifiability.

# Project Objective

Evaluate **IsRel** and **Retrieval** tags quality

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# Dataset: Attributed QA

- Based on Google's Natural Questions (NQ) dataset
- Contains trivia questions written by real Google users
- **Requires knowledge** (e.g., information found on Wikipedia)

## Columns:

- Question
- Passage retrieved by a retriever for that question
- Human annotation indicating whether the passage is relevant to the question
- Other, less relevant, columns like "Generated answer" and etc.

# Setup

- For the entire project we used Google Colab to load Self-RAG system from Huggingface
- Google Colabs L4 and A100 machines were used for 7B and 13B models respectively

# Evaluating “IsRelevant” Tags Family

Called Self-RAG iteratively with the data from Attributed QA dataset:

- Cleaned data - removed duplicate and contradictions
- Question + its respective passage
- Save Self-RAG response + check whether it contains [Relevant] or [Irrelevant] tags
- Compare the result to the human annotation from the dataset (indicating whether the passage is relevant to the question or not)

# Imitating “IsRelevant” Tags Family - Claude

Comparison with state-of-the-art model:

- Chose Claude 3.5 Sonnet for comparison
- One of the most powerful models globally
- Competes and sometimes surpasses GPT-4 in various tasks

# Imitating “IsRelevant” Tags Family - Claude

Claude 3.5 Sonnet evaluation process:

- Used Google Colab notebook for API calls
- Provided the model with the question and the passage
- Asked to determine passage relevance to the question
- Compared results with human annotation from the dataset

# Claude 3.5 Sonnet Prompt

USER



Decide if the following passage <Passage> is relevant for answering the following question <Question>.

Explain your reasoning process, then write the final answer "Yes" or "No" between the tags <Answer> and </Answer>.

Here is the question <Question>: <Question>when does like cage season 2 come out</Question>

Here is the passage <Passage>: <Passage>Title: Luke Cage (season 2)

Section: Release

The second season of Luke Cage was released on June 22, 2018, on the streaming service Netflix worldwide, in Ultra HD 4K and high dynamic range.</Passage>

# Imitating “IsRelevant” Tags Family - Gemma 2 27B

- Free and open SOTA model
- Used RunPod machine with A100 PCIe 80GB
- Evaluation process same as with Claude

# Gemma 2 27B Prompt Template

```
<Q>{question_1}</Q> <P>{passage_1}</P> <A>{human_rating_YES}</A>
<Q>{question_2}</Q> <P>{passage_2}</P> <A>{human_rating_YES}</A>
<Q>{question_3}</Q> <P>{passage_3}</P> <A>{human_rating_NO}</A>
<Q>{question_4}</Q> <P>{passage_4}</P> <A>{human_rating_NO}</A>
<Q>{question_INPUT}</Q> <P>{passage_INPUT}</P> <A>
```



# Evaluating “Retrieval” Tags Family

Decided to continue to another experiment - This time on **Retrieval** family

Working hypothesis:

- Questions from Attributed QA dataset are trivia questions
- We expect a model trained to “choose” whether external information is needed, to generate “Retrieve” token for most, if not all, questions of this type

# Evaluating “Retrieval” Tags Family

Called Self-RAG iteratively with questions from Attributed QA dataset:

- Save Self-RAG response + check whether it contains [Retrieval] or [No Retrieval] tags
- Compare the result to our expectations of high percentage of [Retrieval] and low percentage of [No Retrieval]

# Imitating “Retrieval” Tags Family - Claude

Used Claude 3.5 Sonnet again:

- Provided the model with the question
- Asked to determine if, given a question, there's a need to retrieve information from Wikipedia
- Compared results with our expectations

# Claude 3.5 Sonnet Prompt

## SYSTEM PROMPT

Pretend that you have access to all Wikipedia, so you can use Wikipedia to answer trivia questions

## USER

Decide if you would use Wikipedia to answer the following question <Question>. Write the final answer "Yes" or "No" between the tags <Answer> and </Answer>. Here is the question <Question>: <Question>who played hyde in league of extraordinary gentlemen</Question>

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# Results - “IsRelevant” Tags Family

49.9% match with human rating

		Human Rating	
		Relevant	Irrelevant
Self-RAG 7B	Relevant	2087 (36.1%)	2869 (49.6%)
	Irrelevant	31 (0.5%)	798 (13.8%)

46.8% match with human rating

		Human Rating	
		Relevant	Irrelevant
Self-RAG 13B	Relevant	2080 (36.0%)	3042 (52.6%)
	Irrelevant	38 (0.7%)	625 (10.8%)

**Confusion Matrices: Self-RAG 7B, 13B**

# Results - Imitating “IsRelevant” Tags Family

76.4% match with human rating

		Human Rating	
		Relevant	Irrelevant
Claude 3.5 Sonnet*	Relevant	1932 (33.4%)	1181 (20.4%)
	Irrelevant	186 (3.2%)	2486 (43.0%)

65.34% match with human rating

		Human Rating	
		Relevant	Irrelevant
Gemma 2**	Relevant	467 (16.87%)	279 (10.08%)
	Irrelevant	676 (24.41%)	1342 (48.47%)

**Confusion Matrices:** Gemma-2 and Claude vs Human Ratings

\* Checked 100 examples **without** CoT- results were almost identical

\*\* Gemma-2 might have seen the whole dataset during training

# Results - “Retrieval” Tags Family

	Retrieval	No Retrieval	No tags
<b>Self-RAG 13B</b>	341 (5.9%)	36 (0.6%)	5408 (93.5%)
<b>Claude 3.5 Sonnet</b>	93 (93%)	7 (7%)	-

**Table:** Retrieval Decision Comparison: Self-RAG vs Claude



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## “IsRelevant” Results Analysis

- Self-RAG models have strong bias towards generating “Relevant” tag, at least for Attributed QA dataset

Possible explanations for the **very** poor results:

- User may need to use the same retriever used in the fine-tuning step to avoid poor results
- Maybe more documents per question might increase chances of a good result getting good score
- Problem definition: the task of determining whether a document is relevant to answer a question may not be an easy one, for humans as well.

# “IsRelevant” Results Analysis

Future research:

- Check performance of Llama 2 model (Self-RAG base model) on Attributed QA dataset
- Maybe Self-RAG fine-tuning actually reduced Llama 2 ability to determine relevance

# “Retrieval” Results Analysis

- The model did not behave as expected
- Absence of a Retrieval tag may be interpreted as “No retrieval” (wasn’t mentioned in the paper)
- However, even in this scenario, it still contrary to our expectations
- Maybe the threshold for “Retrieval” tags should be lower

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# Conclusion

- Don't believe to everything you read!
- Claude 3.5 Sonnet is very powerful language model that competes GPT-4
- "Here's the English translation of your Hebrew text, formatted as LaTeX bullet points"

# Code

<https://github.com/stasrodov/self-rag-eval>